MODELO
de Detección Automática Integrado en el Modelo de Usuario

ACACIA

Apoya

ACACIA

Cofinanciado por el programa Erasmus+ de la Unión Europea

Detección automática integrado en el modelo de usuario

Resultado del proyecto ACACIA (561754-EPP-1-2015-1-CO-EPPKA2-CBHE-JP) cofinanciado por el programa Erasmus+ ACACIA: Centros de Cooperación para el Fomento, Fortalecimiento y Transferencia de Buenas Prácticas que Apoyan, Cultivan, Adaptan, Comunican, Innovan y Acogen a la comunidad universitaria.

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Universidad Continental (UC), Perú. INCI: Instituto Nacional para Ciegos de Colombia, Colombia. INSOR: Instituto Nacional para Sordos de Colombia, Colombia. Fundación Sidar Acceso Universal (de ámbito iberoamericano).

1. Index

2. Executive summary

This chapter describes the contents of the deliverable E.5.2.2 "Modelo de detección automática integrado en el modelo de usuario" of ACACIA project.

In this document, it is presented a framework capable of collecting analytic data, from an array of emotions, affects and behaviours, acquired either by human observations, like a teacher in a classroom or a psychologist, or by electronic sensors and automatic analysis software, such as eye tracking devices, emotion detection through automatic facial expression recognition software, among others.

This framework compiles the gathered data in an ontology, and will be able to extract patterns outliers via machine learning, enabling the profiling of the students in critical situations, such as disengagement, attention deficit, drop-out, and other sociological issues, setting real time alerts when these profiles are detected.

The goal is that, by providing insightful real time cognitive data and allowing the profiling of the student's problems, a faster personalized response to help the student is enabled, allowing academic performance improvements.

3. Integrated Model of Automatic Detection in User's Model

5.1. Framework for Student Profile Detection

To tackle the objective of the *Apoya* module, a framework for detecting and managing the students' affective states was developed, considering the usability and implementation needs of the application scenario presented in (Kadar, Calado, 2016), that consists in three case studies for different emotion acquisition technologies and another for an information analysis and reporting system.

5.1.1. Application Scenario

The application scenario proposes a case study for the analysis of gait and posture while the student enters or leaves the classroom, using a 3D motion capture device (i.e. Microsoft Kinect), tracking changes in the regular gait as a indicators of emotional state changes, as studied in (Crane, Gross, 2007; Barliya, Omlor, Giese, Berthoz, Flash, 2013).

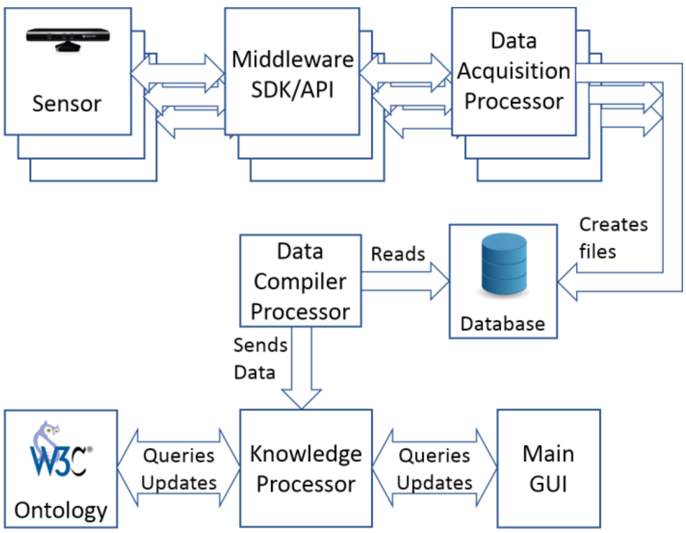
The second case study makes use of an eye tracker to assess the student cognitive activity and engagement level, by tracking the point of gaze in relation to the areas of interest, used for the presentation of didactic content.

The third case study comprises facial recognition algorithms to detect the emotions portrayed by the student during the learning process.

All the data collected is processed and analysed in realtime to a knowledge base that infers from the compiled information, to flag and report students' profile situations indicative of possible academic problems. This is accomplished by an integration platform that manages each student information and records, and provides the teacher with real time alerts of deviations in student's regular patterns, and the possibility to include manual observations.

5.1.2. Framework Design

The proposed framework, illustrated in fig. 1, encompasses the acquisition and processing of the sensors data in a database, the compilation of knowledge sets from the analysis of the database files, the management of that knowledge in an ontology and in the user interface, and the communication between processes.



Gráfica 1 framework Diagram

As described in the application scenario, the student data is captured by the sensors and acquired by the data acquisition processors, through the use of middleware, SDK's or API's, and then written into files in a database. A data compiler processor analyses these files and compiles the resulting knowledge into EmotionML elements that are communicated to the knowledge processor.

The manual annotation of the student status can also be reported, through the main graphical user interface (GUI), to the knowledge processor.

The knowledge processor is responsible for the handling of all the received knowledge and updating it into an ontology, represented by a web ontology language (OWL) knowledge base. The knowledge processor is also responsible for querying the ontology to update the main GUI with the student's record history and to activate the student profile alerts when those profile conditions are detected.

5.1.3. Ontology

The ontology model, used in the framework as a relational knowledge database, was developed based on BROMP, and consists of six primary classes, namely User, Session, Observations, Emotion, Behaviour and Affect. Annex A shows a diagram representation of this Ontology model.

The User class represents the information regarding the student or the teacher.

The Session contains the properties associated with the lecture.

The Observations class is used to describe each individual instance corresponding to an observation period, when information about the student's emotion, behaviour or affect is collected. The Observations instances can be of three sub-class types: Human_Observation (reported manually by the teacher), Digital_Observation (reported automatically by the sensors) and Profiles (which contain the property values that define the necessary conditions to create alerts for each student in each profile situation.

The Emotion class represents the reported emotions and their respective values.

The Behaviour and Affect classes are based in BROMP coding schemes and also contain the properties and respective values that are reported by the observations.

5.1.4. Implementation

One of the sensors used in the implementation was the Gazepoint GP3 eye tracker ("GP3 Eye Tracker", 2016), that has a sample rate of 60Hz and an accuracy between 0.5º and 1º. Because of this device low accuracy, it was only used for behavioural analysis of the student attention, tracking the percentage of time the student looks at their computer screen.

For the automatic detection of emotions the Affectiva SDK (Mcduff, Kaliouby, Senechal, Amr, Cohn, Picard, 2013) was used with the video stream from a webcam. It enables the identification of seven emotions (anger, contempt, disgust, fear, joy, sadness and surprise).

Each sensor data acquisition processor collects the continuous sensor data into XML files, stored in a database. Each file contains the data corresponding to samples recorded for a predefined time. The data acquired from the eye tracker has the following xml format:


```
<REC  TIME="590.59485"  FPOGX="0.47237"  FPOGY=   "0.28856"
FPOGS="590.10193"       FPOGD="0.49292" FPOGID= "937"   FPOGV="1"
(...)   />
```


The data compiler processor then reads each file and extracts the Off_Task behaviour proprieties from the eye tracker files and the emotions proprieties from the Affectiva files. Then a knowledge set is done by averaging the extracted results of each individual file, correspondent to a data acquisition sample time. The knowledge set is communicated to the knowledge processor through TCP sockets using the EmotionML element format. This enables the standardization and interoperability of the framework with other types of sensors and technologies. Each set has the following format:


```
<emotion(…)      start="1234"     duration="130"> <category       name="anger"
        value="0"/>
    <category    name="contempt"  value="0"/>
    <category    name="disgust"   value="0"/>
    <category    name="fear"      value="0"/>
    <category    name="joy"       value="0.25"/>
    <category    name="sadness"   value="0"/>
    <category    name="surprise"  value="0.002"/>
</emotion>
<BEHAVIOUR       start="1234"     duration="130">
    <category    name="Active_Participation"      value=""/>
    <category    name="Disengaged"       value="0.469"/>
    <category    name="Engaged"   value="0.531"/>
    <category    name="Inactive_Participation"    value=""/>
    <category    name="Off_Task"  value=""/>
    <category    name="On_Task"   value=""/>
    <category    name="Other_Behaviour_Name"      value=""/>
    <category    name="Other_Behaviour"   value=""/>

</BEHAVIOUR>
```


The GUI developed allows the teacher to review the student previously recorded Observation data and also the data being recorded in real time. It also offers the possibility for the teacher to provide additional feedback with manual annotations of the observations he/she makes of the student.

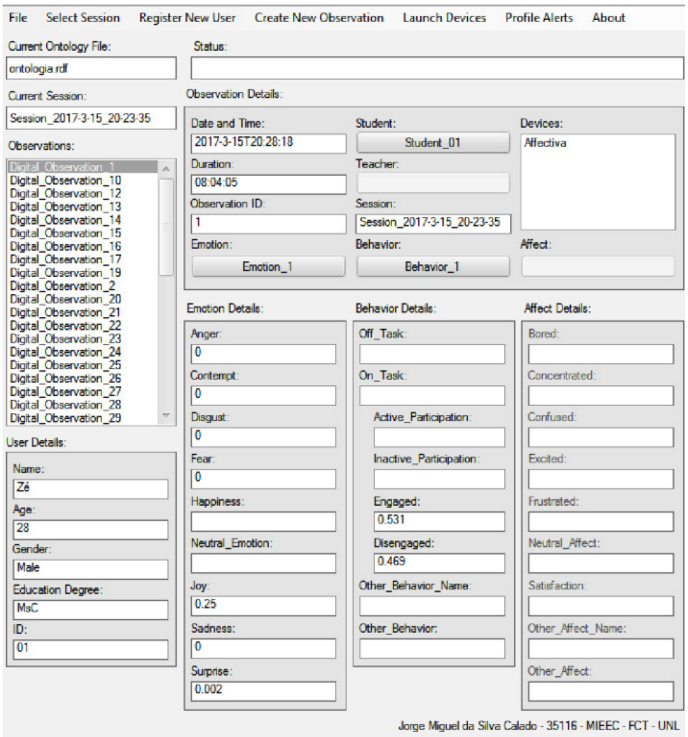


Figure 2 GUI Example

Figure 2 shows an example of the GUI being used to consult a knowledge set of a student observation made with Affectiva.

The first version of the framework implementation produced the real-time alerts only for the attention disorder profile, using predefined thresholds for the Off Task and Disengaged behaviour proprieties, for the Sadness emotion propriety, and setting a minimum number of occurrences of each threshold during the previous 30 minutes.

In future versions, these conditions will be evaluated using machine learning algorithms, suited to each student historic record and detecting patterns deviations as indicators of possible student problems.

4. Conclusions

The student's engagement and learning problems can be mitigated by integrating behavioural and affective detection systems that manage the student's profiles.

This framework details a knowledge-base system capable of interoperability with other systems, for the manual and automatic detection of the student's emotions, behaviours and affective states, and for the pre-emptive and proactive detection of situations consistent with the profiles of student's problems.

This system capability for real-time profile warnings is a valuable asset to assist teachers identifying problems, during the students learning process, and to help in the prevention of school drop-outs.

Additionally, the results of this work also include the paper entitled (available in annex 1):

- A FRAMEWORK TO BRIDGE TEACHERS, STUDENT'S AFFECTIVE STATE, AND IMPROVE ACADEMIC PERFORMANCE

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6. Annex 1 – Paper "A FRAMEWORK TO BRIDGE TEACHERS, STUDENT'S AFFECTIVE STATE, AND IMPROVE ACADEMIC PERFORMANCE"

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A FRAMEWORK TO BRIDGE TEACHERS, STUDENT'S AFFECTIVE STATE, AND IMPROVE ACADEMIC PERFORMANCE

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ABSTRACT

Some of the biggest problems tackling Higher Education Institutions (HEI) are student's drop-out and academic disengagement. Physical or psychological disabilities, socialeconomic or academic marginalization, and emotional and affective problems, are some of the factors that can lead to it.

This problematic is worsened by the shortage of educational resources that can bridge the communication gap between the faculty staff and the affective needs of these students.

In this paper, we present a framework capable of collecting analytic data, from an array of emotions, affects and behaviours, acquired either by human observations, like a teacher in a classroom or a psychologist, or by electronic sensors and automatic analysis software, such as eye tracking devices, emotion detection through automatic facial expression recognition software, among others.

This framework compiles the gathered data in an ontology, and will be able to extract patterns outliers via machine learning, enabling the profiling of the students in critical situations, such as disengagement, attention deficit, drop-out, and other sociological issues, setting real time alerts when these profiles are detected.

The goal is that, by providing insightful real time cognitive data and allowing the profiling of the student's problems, a faster personalized response to help the student is enabled, allowing academic performance improvements.

KEYWORDS

Emotion Detection; Affective State; Behaviour; Eye Tracker; Facial Expression Recognition; Ontology; Machine Learning;

1. INTRODUCTION

A growing problem in HEI is the amount of student dropouts due to disabilities, emotional factors, and economic, social or academic marginalization.

An adapted educational system, which makes use of technology to aid teachers and students, allied with inclusive educational planning and policy-making, may help mitigate these problems.

Technology-enabled environments can help improve the students learning procedure. It could facilitate the access to information and knowledge through adapting its content to any students' profiles and needs. Such approaches can increase their stimulus for learning, and facilitate their communication with teachers, able to motivate an open and inclusive learning process.

1.1 ACACIA

The ACACIA project is a consortium of various higher education institutions, united under the common goal of promoting academic integration, through centres for educational and professional development (CADEP) in Latin America. These centres, comprised in five modules (Empodera, Innova, Cultiva, Apoya and Convoca), articulate with the educational community to detect and support students at risk of academic exclusion, to support and train technical, academic and administrative staff of the institutions, and to make use of technological aids to assist in didactic classes.

The *Apoya* module focuses in the development and implementation of an automated emotion detection and tracking system that allows to monitor and support students, by providing insightful automatic recommendations, with a focus on improving academic performance and reducing school dropouts.

1.2 Outline

This paper outline is as follows: in section 2 a brief stateof-the-art review is made of the human emotions and recognition technologies and methods. In section 3 the framework for student's profile detection is presented, detailing the application scenario, the framework design, the ontology model developed and the implementation of the framework. In section 4 the experiment to test the proof-of-concept prototype is detailed. Finally, in section 5 the final remarks are made and the future work is presented.

2 EMOTIONS

The role emotions play in our daily routines is usually unnoticed, but every action we take is shaped in some way by them, consciously or unconsciously, either by expressing nonverbal communication cues, by influencing our attention or the way we process information and our bias towards it [1], [2].

Although there is no scientific consensus on a single clear definition of emotion, with the term being used in different theories either in a broader or narrower sense, the universality of some emotions (anger, fear, sadness, disgust and enjoyment) is accepted to encompass all humans despite the environmental or sociological background [3].

Despite the lack of consensus on a model that defines what causes emotions, their classification, and their description (categorically or dimensionally), in [4] the author defines a core set of emotion components that are commonly accepted.

2.1 Emotion Recognition

In an emotion analysis environment, like a classroom, a critical problem arises if the student is aware that he is being monitored: his behaviour is going to reflect that knowledge, which often leads to anxiety, insecurity, pretence or other feelings that disguise the regular emotional state, which in turn is a cause for inaccurate measurements.

Thus, when applying technology to assess emotions, the use of a device that causes the least amount of discomfort and distraction is desirable, preferably if it can be concealed from the student attention. This means that biometric sensors traditionally used to detect the emotional state, such as electrocardiogram, electromyogram, galvanic skin response and respiration sensors, are too invasive, due to the requirement of direct contact with the person, disrupting the performance of the activities, thus the more beneficial choice of using contactless sensors, such as facial recognition algorithms and eye tracking devices, being a far more discrete alternative.

When the observation of the emotional state is performed analogically, it is usually accomplished as a self-assessment, made by the person being analysed or by an independent observer that reports the perceived emotional changes. On one hand the self-assessment is subjective to the time it is made and to the emotional state itself, which can lead to biased reports. On the other hand, the observer can only register significant emotional changes, portrayed by the student, and possibly misreading or missing unexpressed internal feelings.

2.2 BROMP

The Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP) [5], offers a methodology to preform quantifiable observations, using different coding schemes to record both behaviour and affect of the student, in a traditional classroom environment.

2.3 Emotion Markup Language

The W3C defined a recommendation called Emotion Markup Language (EmotionML) whose purpose is to serve as a general annotation language of emotion-related states, suitable for systems interoperability and for data representation and processing, usable in manual observations, automatic recognition systems and the generation of systems emotionrelated responses.

2.4 Eye Tracking

Generally used to measure the position and movement of a person's eyes and gaze [6], eye tracking devices can also be employed to correlate gaze fixation time and location, eye blink rate and variations in pupil dilation, with the person cognitive activity and affective states [7], [8].

2.5 Facial Recognition

Facial expression recognition algorithms are being increasingly used as the predominant emotion detection technology, primarily because of the scientific advances in computer vision, using deep learning analysis. Multiple commercial applications offer this technology as API's or SDK's services [9]–[13], capable of reasonably detect the six basic emotions defined by Ekman [14], [15] (anger, disgust, fear, joy, sadness and surprise). **2.6 Existing Technologies**

One of the first projects to include eye tracking technology was "Adaptive e-Learning with Eye tracking" (AdeLE) [16], which analysed eye-movement patterns during learning and tried to link those patterns with cognitive processes.

In [17], the eye tracker is used to adapt presented content to the learner by following his topics of interest.

In [18], a empathic software agent interface was developed using an eye tracker, to infer the focus of attention and motivational status of the learner, responding with instructional behaviours and display of emotion.

The e5Learning learning environment recognizes basic emotion via an eye tracker, assessing "high workload", "nonunderstanding" and "tiredness" situations in order to adapt content presentation in real-time [19].

3 FRAMEWORK FOR STUDENT PROFILE DETECTION

To tackle the objective of the *Apoya* module, a framework for detecting and managing the students' affective states was developed, considering the usability and implementation needs of the application scenario presented in [20], that consists in three case studies for different emotion acquisition technologies and another for an information analysis and reporting system.

3.1 Application Scenario

The application scenario proposes a case study for the analysis of gait and posture while the student enters or leaves the classroom, using a 3D motion capture device (i.e. Microsoft Kinect), tracking changes in the regular gait as a indicators of emotional state changes, as studied in [21], [22].

The second case study makes use of an eye tracker to assess the student cognitive activity and engagement level, by tracking the point of gaze in relation to the areas of interest, used for the presentation of didactic content.

The third case study comprises facial recognition algorithms to detect the emotions portrayed by the student during the learning process.

All the data collected is processed and analysed in realtime to a knowledge base that infers from the compiled information, to flag and report students' profile situations indicative of possible academic problems. This is accomplished by an integration platform that manages each student information and records, and provides the teacher with real time alerts of deviations in student's regular patterns, and the possibility to include manual observations.

3.2 Framework Design

The proposed framework, illustrated in fig. 1, encompasses the acquisition and processing of the sensors data in a database, the compilation of knowledge sets from the analysis of the database files, the management of that knowledge in an ontology and in the user interface, and the communication between processes.

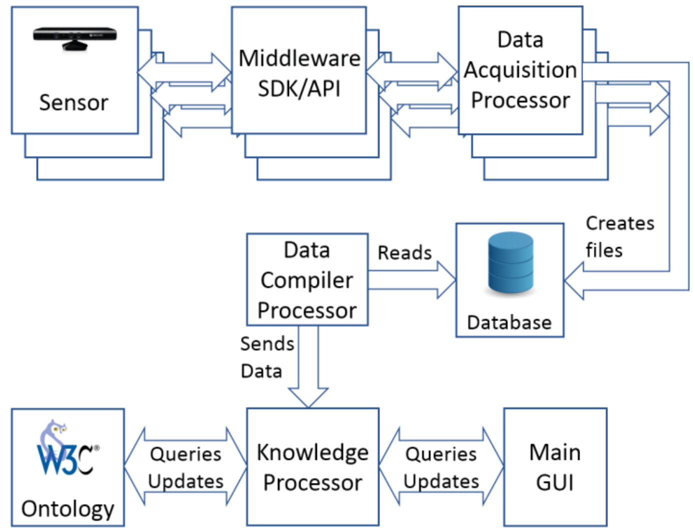

Figure 1 Framework Diagram

As described in the application scenario, the student data is captured by the sensors and acquired by the data acquisition processors, through the use of middleware, SDK's or API's, and then written into files in a database. A data compiler processor analyses these files and compiles the resulting knowledge into EmotionML elements that are communicated to the knowledge processor.

The manual annotation of the student status can also be reported, through the main graphical user interface (GUI), to the knowledge processor.

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3.3 Ontology

The ontology model, used in the framework as a relational knowledge database, was developed based on BROMP, and consists of six primary classes, namely User, Session, Observations, Emotion, Behaviour and Affect. Annex A shows a diagram representation of this Ontology model.

The User class represents the information regarding the student or the teacher.

The Session contains the properties associated with the lecture.

The Observations class is used to describe each individual instance corresponding to an observation period, when information about the student's emotion, behaviour or affect is collected. The Observations instances can be of three sub-class types: Human_Observation (reported manually by the teacher), Digital_Observation (reported automatically by the sensors) and Profiles (which contain the property values that define the necessary conditions to create alerts for each student in each profile situation.

The Emotion class represents the reported emotions and their respective values.

The Behaviour and Affect classes are based in BROMP coding schemes and also contain the properties and respective values that are reported by the observations.

3.4 Implementation

One of the sensors used in the implementation was the Gazepoint GP3 eye tracker [23], that has a sample rate of 60Hz and an accuracy between 0.5º and 1º. Because of this device low accuracy, it was only used for behavioural analysis of the student attention, tracking the percentage of time the student looks at their computer screen.

For the automatic detection of emotions the Affectiva SDK [24] was used with the video stream from a webcam. It enables the identification of seven emotions (anger, contempt, disgust, fear, joy, sadness and surprise).

Each sensor data acquisition processor collects the continuous sensor data into XML files, stored in a database. Each file contains the data corresponding to samples recorded for a predefined time. The data acquired from the eye tracker has the following xml format:

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The data compiler processor then reads each file and extracts the Off_Task behaviour proprieties from the eye tracker files and the emotions proprieties from the Affectiva files. Then a knowledge set is done by averaging the extracted results of each individual file, correspondent to a data acquisition sample time. The knowledge set is communicated to the knowledge processor through TCP sockets using the EmotionML element format. This enables the standardization and interoperability of the framework with other types of sensors and technologies. Each set has the following format:

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        <category       name="anger"
        value="0"/>
    <category   name="contempt"  value="0"/>
    <category   name="disgust"   value="0"/>
    <category   name="fear"      value="0"/>
    <category   name="joy"       value="0.25"/>
```

```
    <category   name="sadness"  value="0"/>
    <category   name="surprise" value="0.002"/>
</emotion>
<BEHAVIOUR      start="1234"    duration="130">
    <category   name="Active_Participation"     value=""/>

    <category   name="Disengaged"       value="0.469"/>
    <category   name="Engaged"  value="0.531"/>
    <category   name="Inactive_Participation"   value=""/>

    <category   name="Off_Task" value=""/>
    <category   name="On_Task"  value=""/>
    <category   name="Other_Behaviour_Name"     value=""/>

    <category   name="Other_Behaviour"  value=""/>
</BEHAVIOUR>
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The GUI developed allows the teacher to review the student previously recorded Observation data and also the data being recorded in real time. It also offers the possibility for the teacher to provide additional feedback with manual annotations of the observations he/she makes of the student.

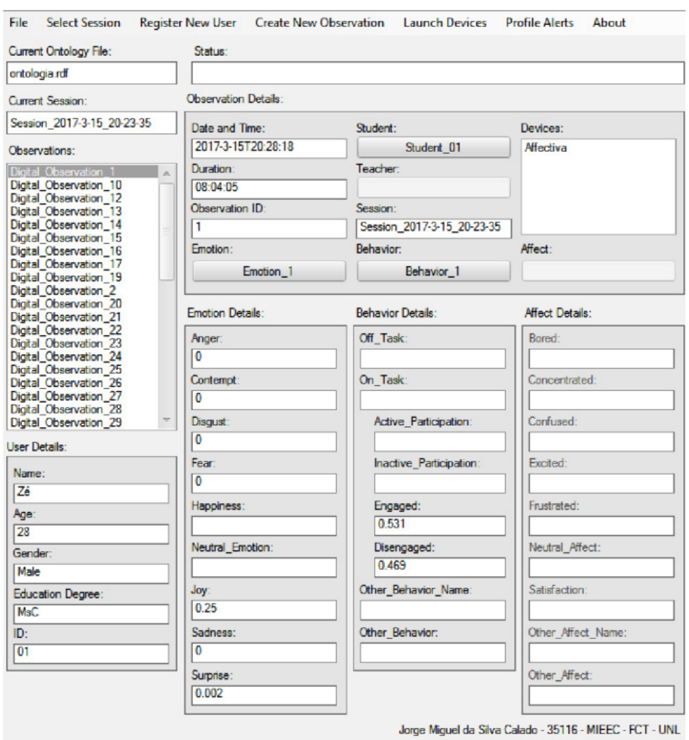

Figure 2 GUI Example

Figure 2 shows an example of the GUI being used to consult a knowledge set of a student observation made with Affectiva.

The first version of the framework implementation produced the real-time alerts only for the attention disorder profile, using predefined thresholds for the Off Task and Disengaged behaviour proprieties, for the Sadness emotion propriety, and setting a minimum number of occurrences of each threshold during the previous 30 minutes.

In future versions, these conditions will be evaluated using machine learning algorithms, suited to each student historic record and detecting patterns deviations as indicators of possible student problems.

4 PROOF-OF-CONCEPT PROTOTYPE

A proof-of-concept test was conducted with 6 participants, 3 male and 3 female, ages 28 to 30. Five participants wore glasses during the tests.

The experiment consisted in a simulated e-learning test, where the participants were asked to read two excerpts of a document in a computer, while their affects, emotions and behaviours were being recorded by sensors and by an observer. The sensors used were the GP3 eye tracker and a webcam, for the Affectiva algorithm, pointed at the participant eyes and face, respectively. The observer, an educational psychologist, made manual annotations of the behaviour and affective state portrayed by each participant during the tests.

During one of the two excerpt readings (chosen randomly) externa stimuli was introduced to distract the participant from the given task, in order to simulate attention problems. Each reading was timed in 10 minutes and in the end of each one a set of 5 questions was asked to the participant, to assess their performance.

All participants read fewer words and performed poorly when answering the questions when they read the excerpt with stimuli, thus validating the premise that their attention was noticeably lower during the reading of the stimulated excerpt. This conclusion was also confirmed by the expert observations.

Having two distinct data sets for different levels of attention, it was then possible to compare between each set, the automatic observation property values collected by the sensors and also the observations made by the expert.

The most significant property values used in this comparison are presented in table 1.

The difference in the Off_Task average values from the sensors, comparing the two excerpt types, ranged between 8.8% and 25.9%.

The analysis to the Emotion properties, detected with the sensors, revealed more significant changes in the average values for Contempt, Joy and Surprise, on most participants.

The change in the average value, between each different reading, was most significant with Joy, ranging between 3.2% and 17.1%. Surprise average values, between each different reading, changed between 1.5% and 6.9%. Contempt average values, between each different reading, changed between 0.8% and 5.9%.

Table 1

Observation Made With:				Affectiva	Eye Tracker	Expert	
Average Values (0-1 range)	Participant	Excerpt	Stimuli	Emotion	Behaviour	Emotion	Behaviour
				Joy	Off_Task	Joy	Off_Task
	1	A	No	0.0208	0.2146	0.0000	0.0000
		B	Yes	0.1522	0.3510	0.0545	0.1727
	2	A	Yes	0.0316	0.3900	0.1455	0.1818
		B	No	0.0000	0.2949	0.0000	0.0000
	3	A	No	0.0000	0.2650	0.0000	0.0000
		B	Yes	0.1220	0.3536	0.0909	0.3909
	4	A	Yes	0.0621	0.4230	0.0364	0.2727
		B	No	0.0269	0.1632	0.0909	0.0000
	5	A	No	0.0016	0.2535	0.0000	0.0000
		B	Yes	0.0958	0.3748	0.1182	0.2636
	6	A	Yes	0.1712	0.4116	0.0000	0.3818
		B	No	0.0000	0.2944	0.0000	0.0000

Comparing the emotions detected through the sensors with the observations made by the expert, the average values for Joy were analogous, while the other emotions were not, in part because the expert did not recognize their manifestation.

This early testing enabled the validation of the hypothesis that the Off_Task behaviour property and the Joy emotion property are suitable classifiers for the attempt to detect attention deficits.

5 CONCLUDING REMARKS AND FUTURE WORK

As society shifts to a technology aided environment, the student's engagement and learning problems can be mitigated by integrating behavioural and affective detection systems that manage the student's profiles.

This framework details a knowledge-base system capable of interoperability with other systems, for the manual and automatic detection of the student's emotions, behaviours and affective states, and for the pre-emptive and proactive detection of situations consistent with the profiles of student's problems.

This system capability for real-time profile warnings is a valuable asset to assist teachers identifying problems, during the students learning process, and to help in the prevention of school drop-outs.

In future work, additional student profiles will be included, depicting different problems, as well as the integration of machine learning algorithms to detect pattern outliers and set corresponding profile suggestions and alerts.

A future step in scientific validation will be the deployment in a larger environment, like a real classroom, where a more significant amount of data could be collected, further improving the machine learning dataset and, subsequently, the detection algorithm itself.

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ANNEX A

ONTOLOGY MODEL DIAGRAM